Bleeding segmentation of surgical images

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Project introduction

- Main purpose

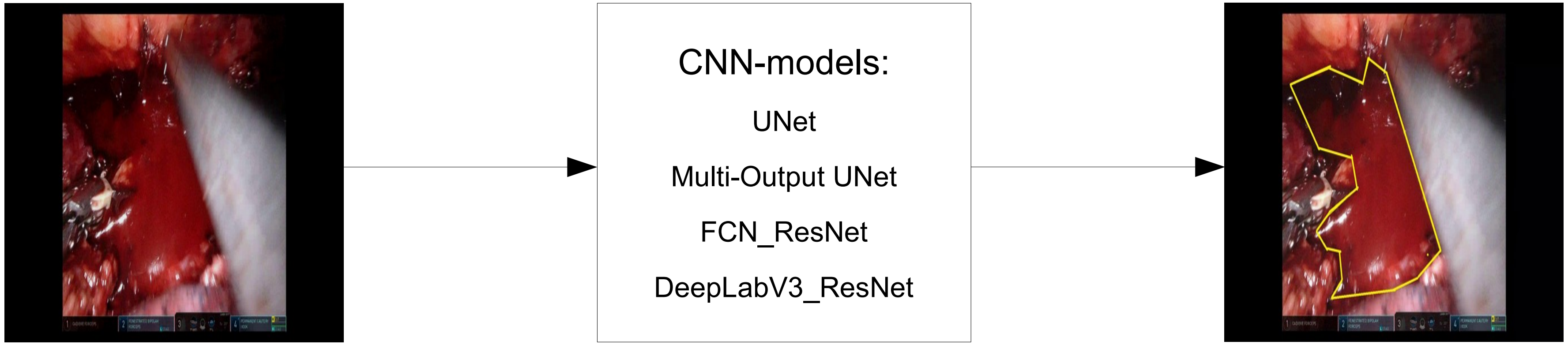


Fig 1. Segmentation process

- Evaluation methods

    dice loss, precision, recall, specificity, f_1

Dataset

- Origional images

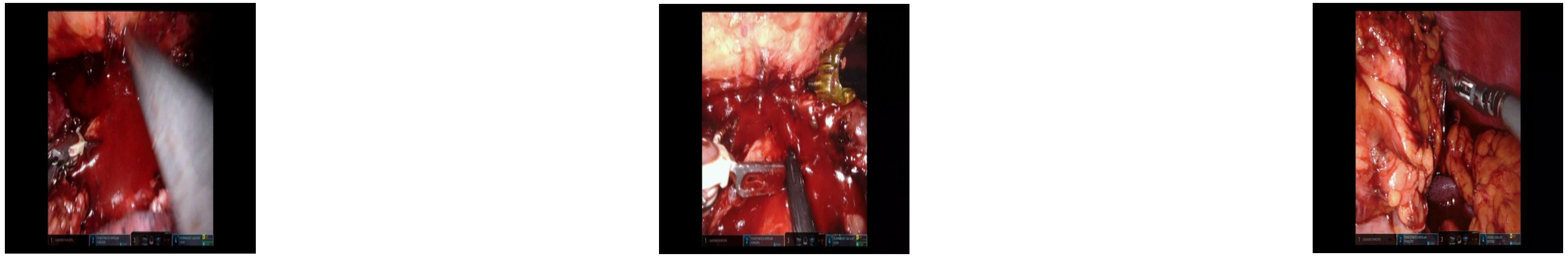


Fig 2. original surgical images

- Polygon annotations

In form of: $[(x_0,y_0), (x_1,y_1), \ldots (x_n,y_n)]$

- Generated masks

Fig 3. generated masks

Dataset

- Size
  - Number of surgeries: 9
  - Number of images **WITH** blood: 946 (70%)
  - Number of images **WITHOUT** blood: 405 (30%)

- K-Ford validation (k=5) grouping rules
  - Absolutely separated training and evaluation sets
  - Minimum difference between size of groups

- Validation group size

  [250, 250, 250, 250, 250]

Pre-Process

- Random-crop and flip (all models)

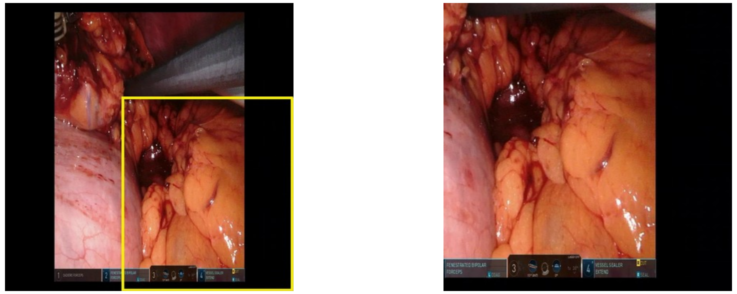


Fig 4. random crop

RandomResizedCrop((256, 256), scale=(0.5, 1.0))

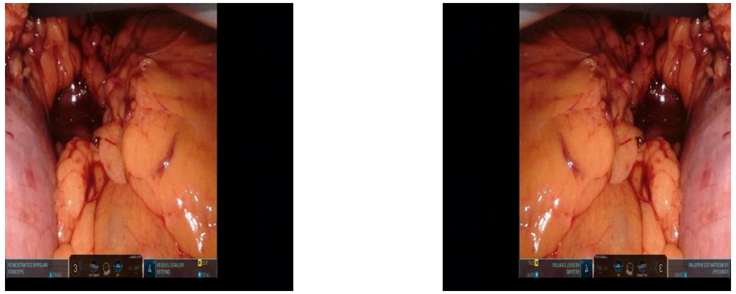


Fig 5. random flip

RandomHorizontalFlip()

- Normalisation (ResNet only)

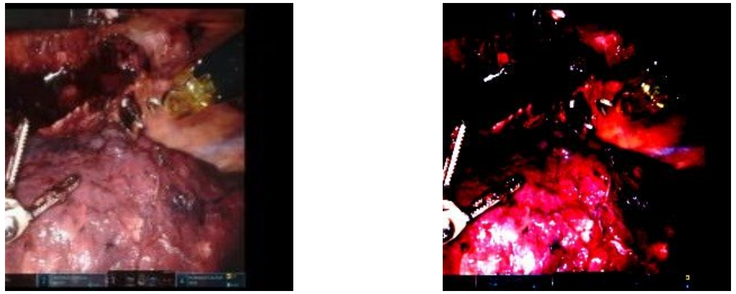


Fig 6. normalization

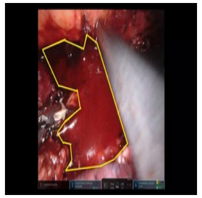
```
Normalize(   mean  = [0.485, 0.456, 0.406],
             std   = [0.229, 0.224, 0.225]     )
```

Evaluation methods

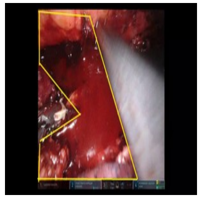
- Dice loss

$$DiceLoss(I_m, I_e) = 1 - \frac{2 \times TP(I_m, I_e) + s}{Positiv(I_m) + Positiv(I_e) + s}$$

- $TP(I_m, I_e) = \sum_{x, y \in (0, 255)} I_m(x, y) \times I_e(x, y)$
- $Positiv(I) = \sum_{x, y \in (0, 255)} I(x, y)$

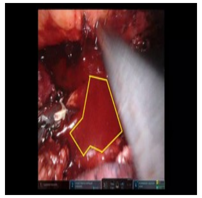


ground truth



too large

$Positiv(I_e)\ \uparrow$ $DiceLoss(I_m, I_e) \uparrow$



too small

$Positiv(I_e)\ \downarrow$
$TP(I_m, I_e)\ \downarrow\downarrow$ $DiceLoss(I_m, I_e) \uparrow$

Fig 7. estimation group

Evaluation methods

- Confusion matrix

		Real category	
		Positive	Negative
Estimation	Positive	**TP**	**FP**
	Negative	**FN**	**TN**

- Measurments

$$\boldsymbol{precision} = \frac{TP}{TP+FP}$$

$$specificity = \frac{TN}{TN+FP}$$

$$recall = \frac{TP}{TP+FN}$$

$$f_1 = \frac{2 \times precision \times recall}{precision + recall}$$

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Models

- Convolution unit

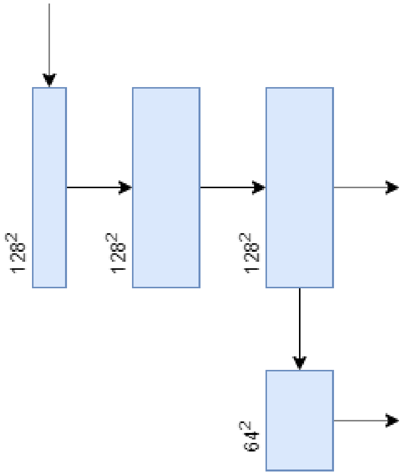

Fig 8. down sampling unit

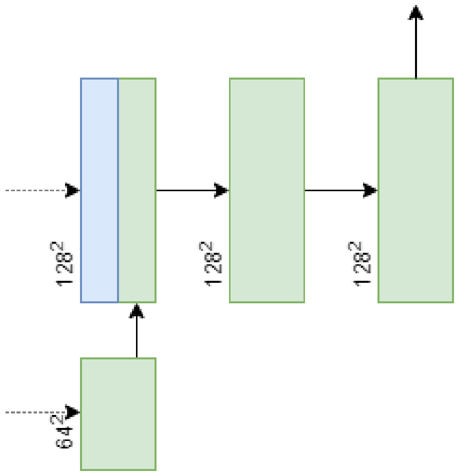

Fig 9. down sampling unit

Models

- UNet

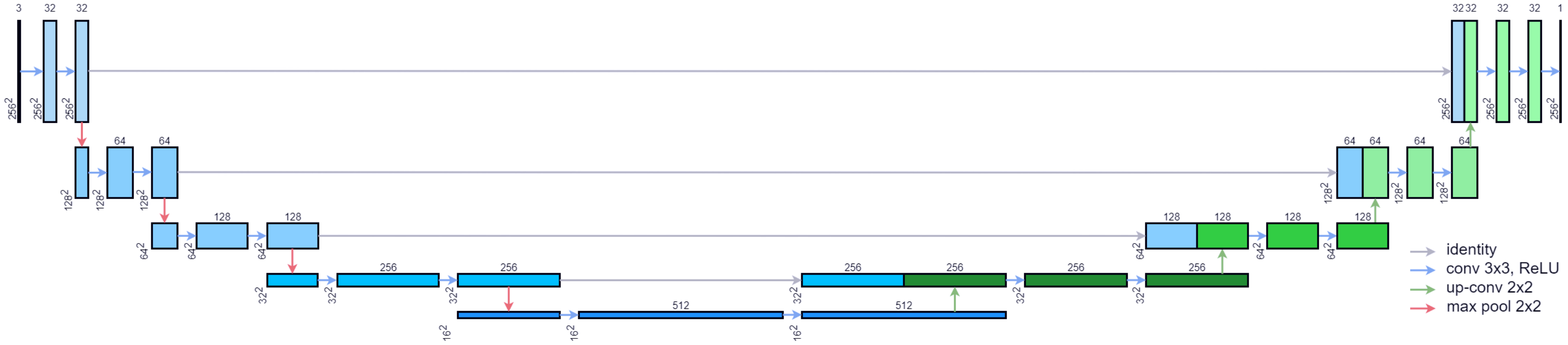

Fig 10. UNet model structure.

Adapted from: [1] Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation.

$$Loss(I_m, I_e) = DiceLoss(I_m, I_e)$$

Models

- Multi-Output UNet

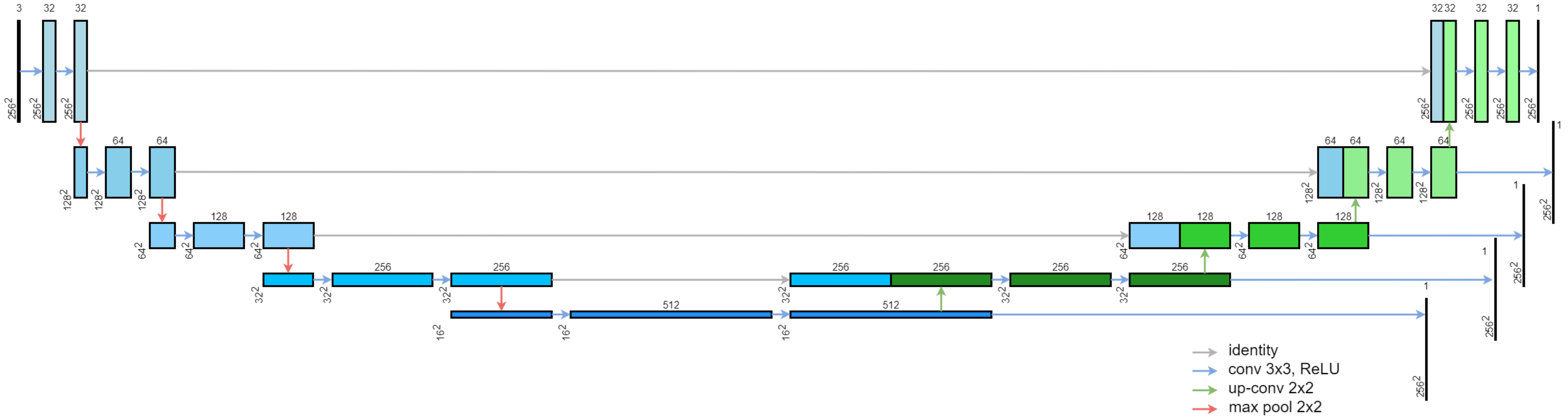

Fig 11. Multi-OutputUNet model structure.

Idea from: [2] Sun, Tao, et al. ”Stacked U-Nets With Multi-Output for Road Extraction.” CVPR Workshops. 2018.

$$Loss(I_m, I_i \in [0,4]) = \frac{\sum_{i \in [0,4]} DiceLoss(I_m, I_i)}{5}$$

Models

- Learning rate

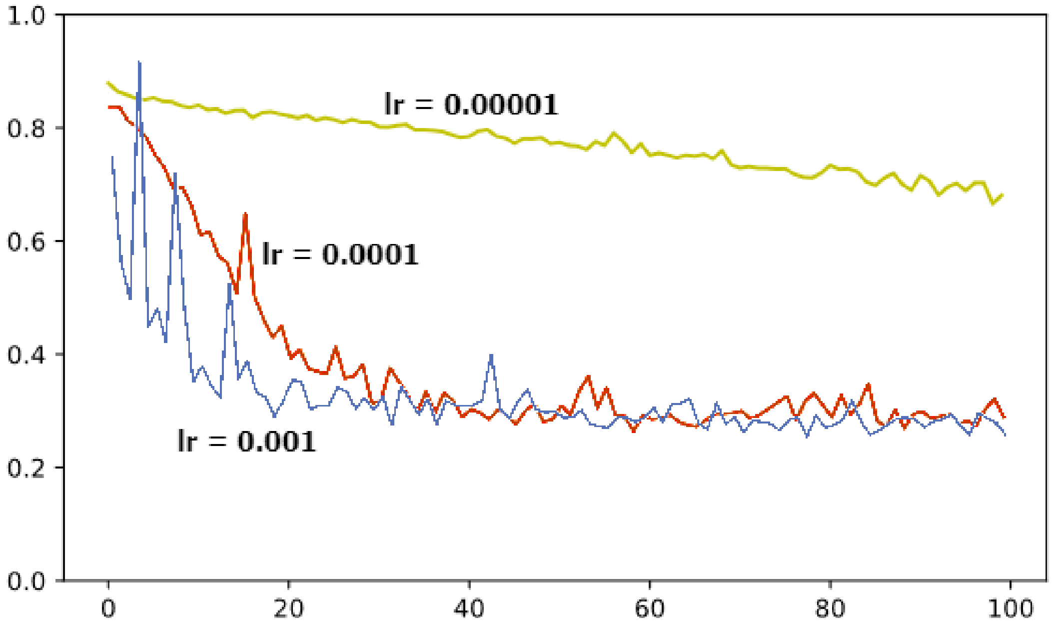

Fig 12. Curve of loss with different learning rate

Results

- Training curve

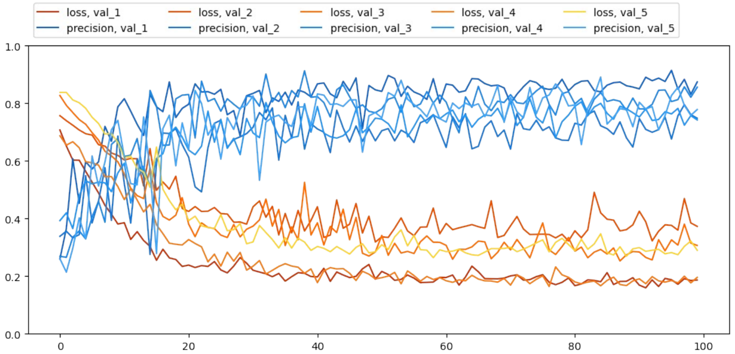

Fig. 13: Evaluation curve of UNet

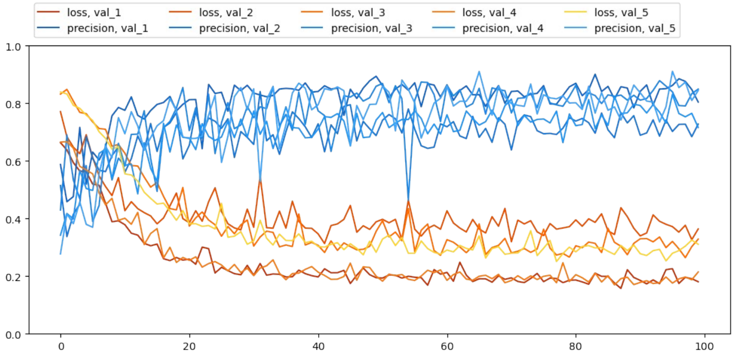

Fig. 14: Evaluation curve of Multi-Output UNet

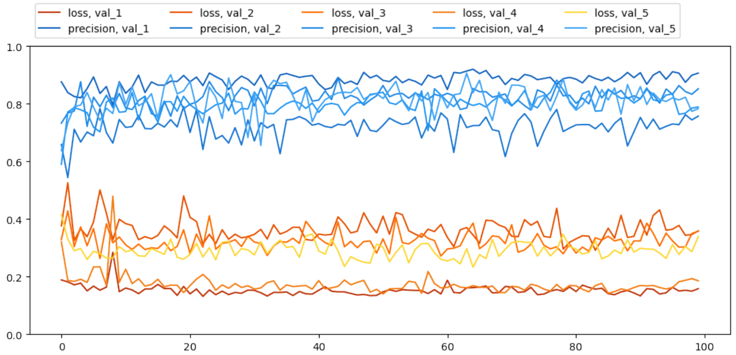

Fig. 15: Evaluation curve of FCN ResNet50

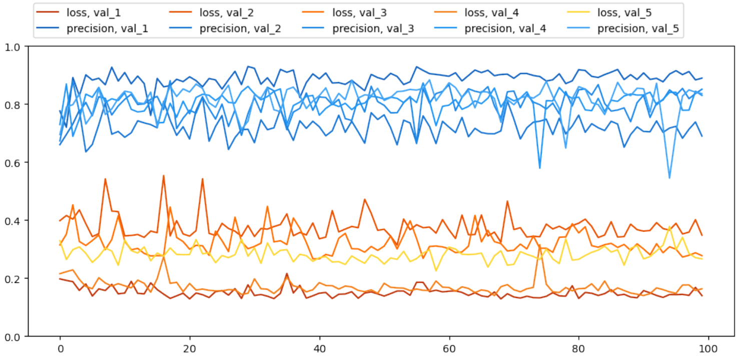

Fig. 16: Evaluation curve of DeepLabV3 ResNet50

Results

- Model estimations

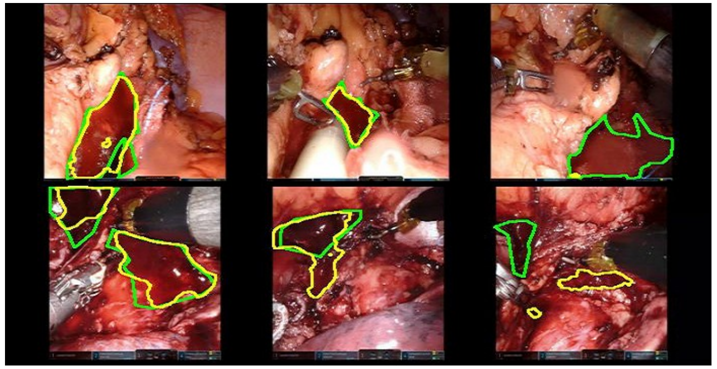

Fig. 17: Evaluation curve of UNet

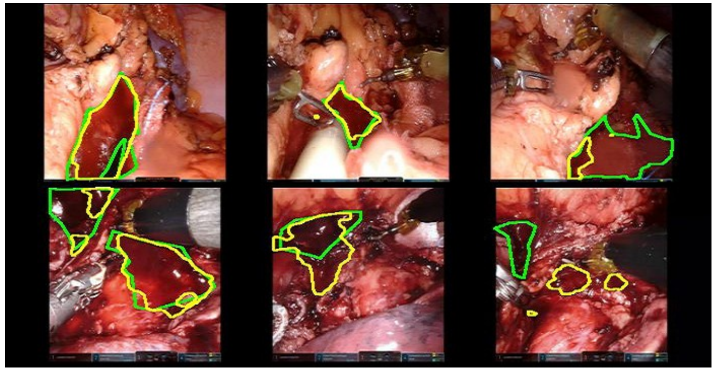

Fig. 18: Evaluation curve of Multi-Output UNet

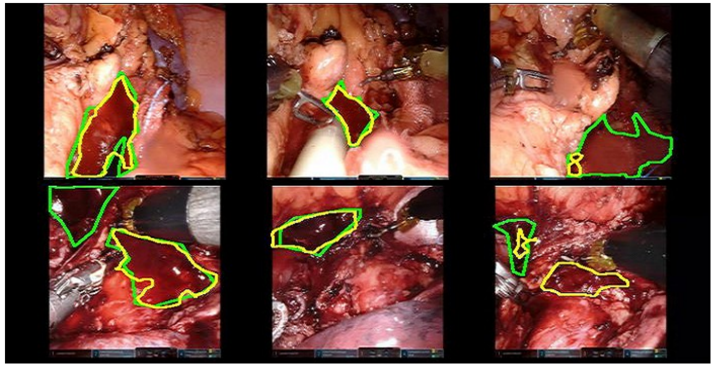

Fig. 19: Evaluation curve of FCN ResNet50

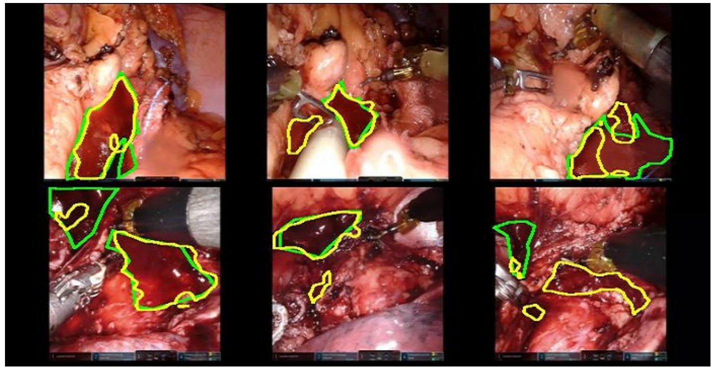

Fig. 20: Evaluation curve of DeepLabV3 ResNet50

Results

- Evaluation data and statistic

	loss	precision	recall	specificity	f_1
cross_val 1	0.1865	0.8739	0.7618	0.9896	0.8135
cross_val 2	0.3727	0.7479	0.5571	0.9848	0.6273
cross_val 3	0.3065	0.8558	0.5912	0.9956	0.6935
cross_val 4	0.1958	0.7421	0.8942	0.9672	0.8042
cross_val 5	0.2897	0.7781	0.6560	0.9918	0.7103
average	0.2702	0.7996	0.6920	0.9858	0.7298

Fig. 21: Evaluation curve of UNet

	loss	precision	recall	specificity	f_1
cross_val 1	0.1806	0.8042	0.8409	0.9782	0.8194
cross_val 2	0.3637	0.7276	0.5727	0.9824	0.6363
cross_val 3	0.3284	0.8490	0.5691	0.9954	0.6716
cross_val 4	0.2144	0.7159	0.8763	0.9644	0.7856
cross_val 5	0.3107	0.8441	0.5859	0.9955	0.6892
average	0.2796	0.7882	0.6890	0.9832	0.7204

Fig. 22: Evaluation curve of Multi-Output UNet

	loss	precision	recall	specificity	f_1
cross_val 1	0.1582	0.9062	0.7875	0.9917	0.8418
cross_val 2	0.3586	0.7570	0.5697	0.9850	0.6414
cross_val 3	0.3576	0.8517	0.5684	0.9954	0.6424
cross_val 4	0.1856	0.7889	0.8818	0.9745	0.8144
cross_val 5	0.3386	0.7830	0.6201	0.9925	0.6614
average	0.2797	0.8173	0.6855	0.9878	0.7203

Fig. 23: Evaluation curve of FCN ResNet50

	loss	precision	recall	specificity	f_1
cross_val 1	0.1395	0.8891	0.8406	0.9892	0.8605
cross_val 2	0.3478	0.6894	0.6597	0.9754	0.6522
cross_val 3	0.2772	0.8508	0.6857	0.9942	0.7228
cross_val 4	0.1630	0.8296	0.8807	0.9811	0.8370
cross_val 5	0.2662	0.8358	0.6541	0.9939	0.7338
average	0.2387	0.8189	0.7442	0.9868	0.7613

Fig. 24: Evaluation curve of DeepLabV3 ResNet50

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Results

- Response time

	CPU (i7-6700k)	GPU (GeForce RTX 2070)
UNet	110ms (9.09 fps)	2.5ms (400 fps)
Multi-Output UNet	110ms (9.09 fps)	2.8ms (357 fps)
FCN_ResNet50	270ms (3.70 fps)	5.8ms (172 fps)
DeepLabV3_ResNet50	440ms (2.27 fps)	6.2ms (161 fps)

Fig. 25: Response time of different model

Conclution

	Loss	Stability	Response Time
UNet	medium	medium-low	short
Multi-Out UNet	medium	medium	short
FCN ResNet	medium	medium	long
DeepLab ResNet	medium	medium	long

Reference

[1] Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation.

[2] Sun, Tao, et al. ”Stacked U-Nets With Multi-Output for Road Extraction.” CVPR Workshops. 2018.